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OPTIMISATION OF PARAMETERS FOR IMPROVING DIMENSIONAL ACCURACY IN CNC MACHINING

B. Ramamoorthy [1], V. Radhakrishnan [1] and A. Weckenmann [2]
[1]Manufacturing Engineering Section, Department of Mechanical Engineering
Indian Institute of Technology, Madras, India
[2] Department of Quality Management and Manufacturing Metrology
University of Erlangen-Nuremberg, Germany

Abstract: The objective of this work is to demonstrate how the single hidden layer Multilayer Perceptron (MLP) neural network could be used to model a typical NC turning process. The Network configuration was decided after performing many trials, and then a generalized MLP neural network with a single hidden layer was used to establish the process model with the available experimental data. The neural network was then used to predict the diameter error and the cutting force for different operating conditions and the testing process was conducted. From the results obtained it was found that the predicted values were within the allowable error tolerance. Therefore, it was found that the implemented single hidden layer back propagated Neural Network approach yields a relatively more accurate process model for the turning process.

Keywords: Turning operation, Artificial Neural networks, Single Hidden Layer Perceptron, Back propagation

1 INTRODUCTION

Manufacturing engineering has wide variety of machining processes, which are very complicated to analyze directly. Therefore it is important to create process models, which can be either analytic or stochastic models. These models are then used for optimization purposes, but it is difficult to adjust the parameters on-line according to the actual situation of the machining process. Therefore, the processes cannot be controlled adaptively to attain optimal conditions such as maximum production rate, minimum cost per piece and minimum tool wear rate.

Since Artificial Intelligence techniques are insensitive to the noise induced in the machining data, caused by the variations in other parameters such as material properties, temperature and cutting geometry, most of the current researches are carried out by adopting these techniques for modeling and control of machining processes. Chryssolouris and Guillot [1] evaluated different process modeling techniques and concluded that a proper Neural Network model can best estimate the operating parameter values. Rangwala and Dornfield [2] used Neural Network to learn and optimize the turning process using a conventional optimization approach. Artificial Neural Networks are nonlinear, in that they can capture complex interactions among the input variables in a system. In a linear system, changing a single input produces a property change in the output and the effects of input parameters depend only on their own value [3]. In a non-linear system, the effect depends on the values of other inputs and the relationship is of higher order functions.

The aim of this paper is to show that the turning process could be modeled and controlled entirely by backpropagated neural network. Although work in the past was carried out with multi-layered perceptrons using three hidden layers [4], and here a simple network with a single hidden layer is tried out to generalize and model the turning process under given tolerance levels. The Network configuration and parameters were selected on the basis of their performance and influence on the machining operation respectively [5]. The effect of optimum learning rate and the momentum factor on the convergence of the network were also studied. The process modeling methodology used [6] is as follows, Initially a generalized backpropagated neural network with a single hidden layer, is used to establish the process model with available experimental data, by training it with a set of 30 patterns. Then the neural network was used to predict the diameter error and the cutting force during operation for known operating parameter values and later tested for 10 fresh patterns. From the results of the implemented approach, it was found that the neural network representation was effective for the process modeling and optimization procedure.

2 EXPERIMENTS AND OBSERVATIONS

The turning process was performed in a DENFORD ZEROTURN two axis CNC lathe. Aluminum rods of 38 mm diameter were machined to varying diameters of 20 mm, 25 mm, 30 mm and 35 mm The input variables are spindle speed, depth of cut, feed rate, diameter of workpiece, length of cut and clamping length. The outputs of the neural network system are the diameter error, which indicate the accuracy attainable during the machining process and the cutting force, which is an indicator of the machinablity of the workpiece material. The KEMCO three axes pneumatically controlled bridge type CMM was used to take dimensional and form measurements. The measured values are given in table 1 and 2.

3 NEURAL NETWORKS AS ERROR PREDICTION TOOL

In the present work, Multilayer Perceptrons with each layer consisting of a number of computing neurons have been used. The general architecture of a 3-layered Multilayer Perceptrons [MLP] consists of input layer, an output layer and a single hidden layer. MLP uses Back-Propagation Algorithm (BPA) for training the network in a supervised manner. BPA is a steepest-descent method, where weight values are adjusted in an iterative fashion while moving along the error surface to arrive at minimal range of error, when input patterns are presented to the network for learning. The learning process consists of a forward pass, in which the input pattern is applied to the nodes of the input layer and its effect propagates layer by layer through the network. The difference between the network output and the desired output is propagated back during the backward pass to update the synaptic weights. The weights are updated every time the input patterns are presented to the network and this continues till the network output comes closer to the desired output.

$$\Delta R\ (T+1) = -\eta\ \delta\ Ep / \delta\ R + \gamma * \Delta R(T) \tag{1}$$

where γ is the momentum factor with value $0 <= \gamma <= 1$.

3.1 Process modeling methodology

In the modeling procedure, inputs are fixed and network parameters are adjusted to minimize the summation of the square of the error E, which is the difference between the desired output, T_j, and the actual output, O_j. This study also aims at optimizing the structure of the neural network to a single hidden layer and an optimum number of hidden nodes. In using BP neural networks for modeling the turning process, initially the network topology is decided, i.e. number of hidden layers and number of neurons in each layer. In a BPA generally one hidden layer is enough for most of the applications, because it can form arbitrary mapping between a set of given inputs and outputs. A set of experimental values is used, which have the largest deviation from the mean as the training data for performing the learning procedure. So 30 patterns are used for training and 5 patterns for testing the ANN. The thresholding function used in the back propagation algorithm is the Sigmoid non-linear function shown below.

$$F\ (x) = 1 / \exp(-x) \tag{2}$$

3.2 Training and testing the network

In the present work, six inputs and two outputs were chosen. The inputs are spindle speed, feed rate, depth of cut, clamping length, diameter of the part and length of machining. The outputs are cutting force and diameter error. The patterns presented to the network were first normalized before submitting to the network
For normalizing the input patterns the following relation was used,

$$X_i = \frac{X_i}{\sqrt{\left(X_1^{\,2} + X_2^{\,2} + \ldots + X_n^{\,2}\right)}} \tag{3}$$

For normalizing the output values,

$$X_i = \frac{X_i}{X_{\max}} \tag{4}$$

After performing many trials with different configurations Fig (1), the configuration 6--9--2 gave the best results in terms of convergence rate and network size. To find out the minimum training error configuration, number of hidden nodes, learning rate (η)and momentum factor (β) were varied from 1 to 35, 0.05 to 1, 0.05 to 0.9 respectively. The optimum number of hidden nodes required for getting the minimum error tolerance was found to be 9 nodes Fig (2) and the optimum learning rate for the network to obtain minimum average error was 0.6 Fig (3).

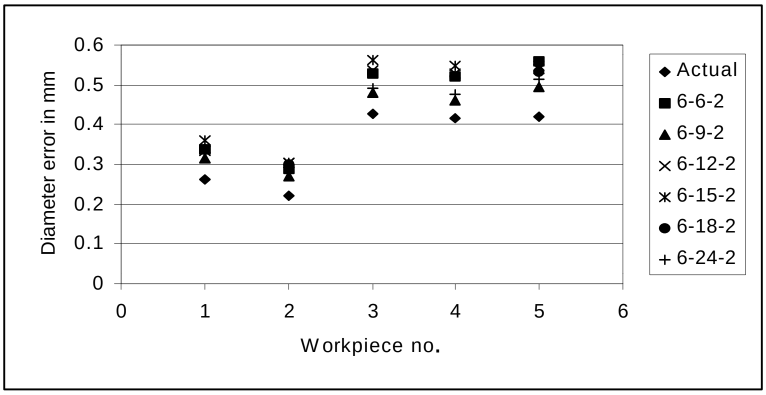

Figure 1. Performance of different configurations.

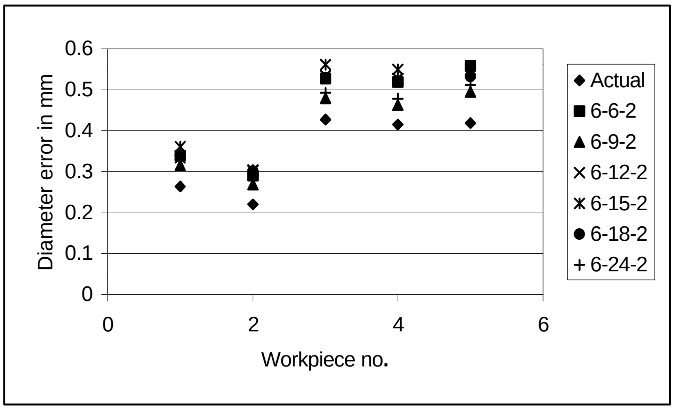

Figure 2. Effect of No. Hidden Nodes on the Error for 50k cycles

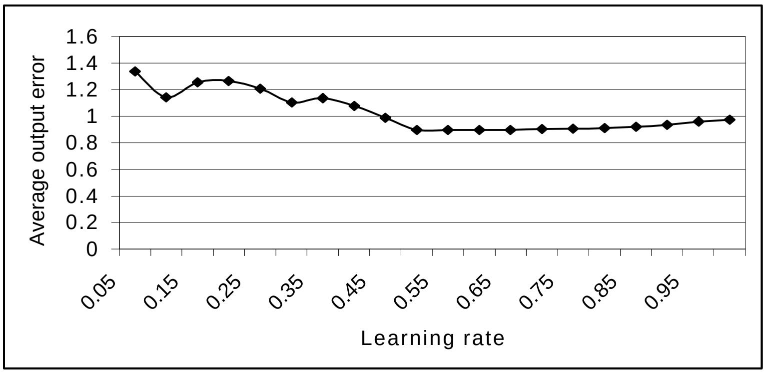

Figure 3. Effect of Learning rate on Average Error

The network configuration selected gave good results and achieved an error per cycle of about 0.08. Workpieces were machined to the same part geometry and their dimensions were measured using the Kemco CMM The form error was measured along the planes as shown in fig (4). The operating conditions were submitted to the neural network for prediction of the diameter error and the cutting force. Comparison of the output shows that the difference was insignificant. Hence it can be interpreted that the neural network can be used for the correction of the NC program with reasonable accuracy.

4 ANALYSIS OF RESULTS

The results of the turning operation experiments [Table 1], diameter and form error measurements [Table 2] and the neural network trials [Table 3] were analyzed to determine the various effects of the operating parameters and the influence of the learning rate parameter and the momentum rate factor on the convergence of the network.

Table1. Experimental parameter values and Forces measured

Workpiece no	Clamping length in mm	Feed rate in mm	Depth of cut in mm	Spindle speed in rpm	Cutting force F_C in kgf	Feed force F_A in kgf
1	50	0.05	0.2	1000	0.846	0.5859
2	50	0.05	0.25	1000	0.972	0.5859
3	50	0.1	0.25	1000	1.269	0.7812
4	50	0.1	0.25	1200	1.368	0.9765
5	70	0.1	0.25	1200	1.128	0.7812
6	70	0.1	0.25	1200	1.551	0.7812
7	70	0.15	0.25	1200	1.692	0.5859
8	90	0.15	0.3	1200	1.833	0.9765
9	90	0.15	0.3	1600	1.974	0.9765
10	90	0.2	0.4	1600	2.155	1.1782

Table 2. Diameter and Form error measurements

Sl.no	Diameter error in mm.				Form error in mm.			
Work Piece no	20mmϕ Cyl	25mmϕ Cyl	30mm ϕ Cyl	35mm ϕ Cyl	Plane 1	Plane2	Plane3	Plane 4
1	.252	.270	.216	.055	.062	.022	.019	.035
2	.116	.025	.078	.048	.073	.025	.00	.001
3	.129	.156	.113	.167	.031	.044	.004	.043
4	.124	.202	.142	.067	.064	.022	.0	.014
5	.012	.296	.296	.172	.017	.032	.032	.002
6	.071	.100	.101	.081	074	.021	.022	.017
7	.223	.310	.243	.182	.081	.031	.004	.014
8	.128	.254	.301	.292	.055	.021	.025	.005
9	.062	.099	.020	.186	.087	.032	.017	.020
10	.003	.013	.155	.295	.021	.011	.004	.023

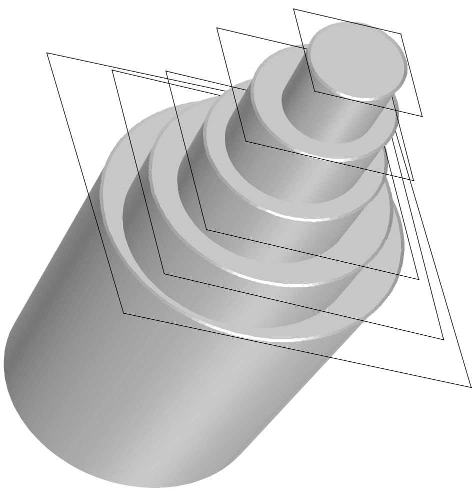

Figure 4. Planes along which the Form errors were measured

Table 3. Output of different ANN configurations for test workpieces

Sl. No	Actual dia. Error	Diameter error Output of ANN					
		6 –6---2	**6—9—2**	6—12—2	6—15—2	6—18—2	6—24---2
1	0.42756	0.5275	**0.4788**	0.5344	0.5614	0.5287	0.4921
2	0.41477	0.5195	**0.4624**	0.5280	0.5487	0.5213	0.4780
3	0.41903	0.5580	**0.4944**	0.5486	0.5404	0.5328	0.5122
4	0.26420	0.3385	**0.3155**	0.3341	0.3605	0.3386	0.3287
5	0.22017	0.2906	**0.2688**	0.3021	0.3032	0.3012	0.2933

Table 4. Comparison of Actual and ANN output values for the Configuration 6—9—2

Workpiece No	Experimental values		ANN output values		Prediction Error in %	
	Diameter error in mm	Cutting force F_C in kgf	Diameter error in mm	Cutting force Fc in Kgf	Diameter error	Cutting force error
1	0.2898	0.4248	0.264	0.4885	8.9	15
1	0.3384	0.2427	0.288	0.2894	14.89	19.24
1	0.1485	0.2731	0.147	0.3025	10.09	10.77
1	0.1426	0.3641	0.136	0.4257	4.62	16.92
2	0.0138	0.3338	0.0182	0.3508	24.64	5.1
2	0.08165	0.3945	0.0853	0.4531	4.47	14.85
2	0.25645	0.1821	0.237	0.2081	7.58	14.28
2	0.2967	0.1517	0.279	0.1756	5.69	15.75
3	0.0703	0.1517	0.078	0.1736	10.95	14.44
3	0.0345	0.4542	0.027	0.5245	21.74	7.3

4.1 Neural net output analysis

By selecting the network parameters like the learning rate parameter η=0.6 and the momentum factor γ=0.9 and by setting the permitted maximum total absolute error for each pre-normalized input-output pair equal to 0.05 the training process for the network was implemented. It was noted that the values of the feed rate and the depth of cut influenced the number of iterations required to train the network.

Table 5. Effect of Learning rate and Momentum factor on the network performance

SL.No	Learning rate (η)	Momentum Factor (β)	Number of cycles	Training Error
1	0.3	0.3	25000	1.3368
2	0.3	0.5	25000	1.1424
3	0.3	0.9	25000	1.0256
4	0.5	0.3	25000	1.2646
5	0.5	0.5	25000	1.2078
6	0.5	0.9	25000	1.1038
7	0.6	0.2	25000	1.1342
8	0.6	0.3	25000	1.0762
9	0.6	0.5	25000	0.9875
10	**0.6**	**0.9**	**25000**	**0.8982**
11	0.7	0.5	25000	0.9932
12	0.7	0.9	25000	0.1044
13	0.8	0.5	25000	0.1072
14	0.8	0.9	25000	0.1094
15	0.9	0.5	25000	0.1100

4.2 Observations and Discussion

The tangential cutting force and the diameter error observed during the experiments were plotted against the operating parameters. The graphical representations of these experimental observations indicate a definite correlation between the factor under consideration and their response. The cutting force was found to be increasing with the increase in depth of cut and feed rate used [Fig (5) & (6)]. The Diameter error is the difference between the diameter programmed in the NC program and the actual diameter obtained after the turning operation is performed. The Diameter error was also found to be increasing along with an increase in the feed rate and depth of cut [Fig (7) & (8)].The cutting force was found to be decreasing with increase of spindle speed [Fig (9)]. The results obtained from the measurement of the machined components were analyzed. Deviations in the nominal diameter of the machined components from the programmed dimensions were found to follow some particular pattern. It was found that the diameter error increases with the increase in the diameter machined on the part,

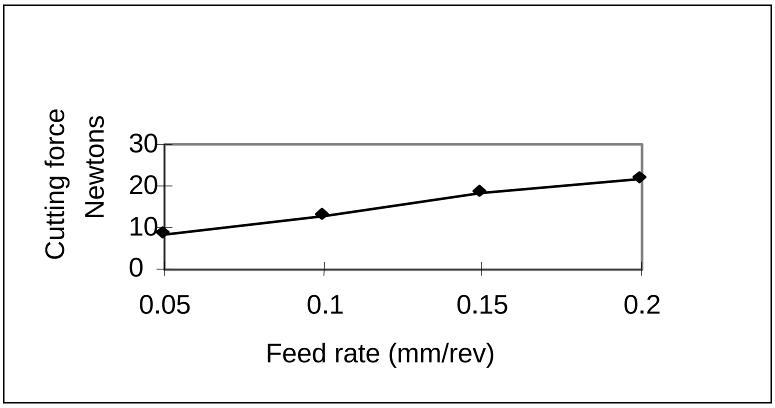

Figure 5. Effect of feed rate on cutting force.

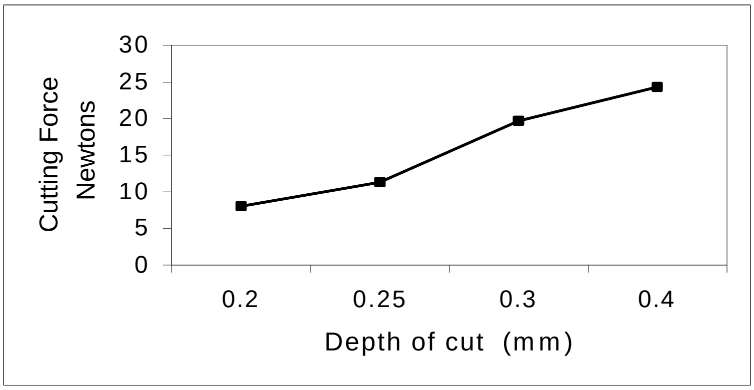

Figure 6. Effect of Depth of cut on cutting force

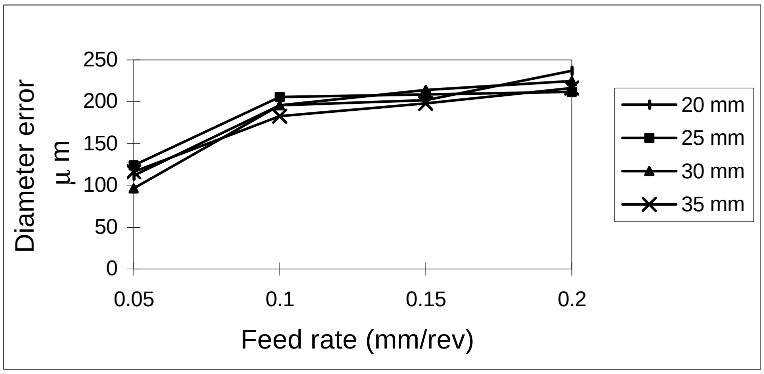

Figure 7. Effect of Feed rate on Diameter error

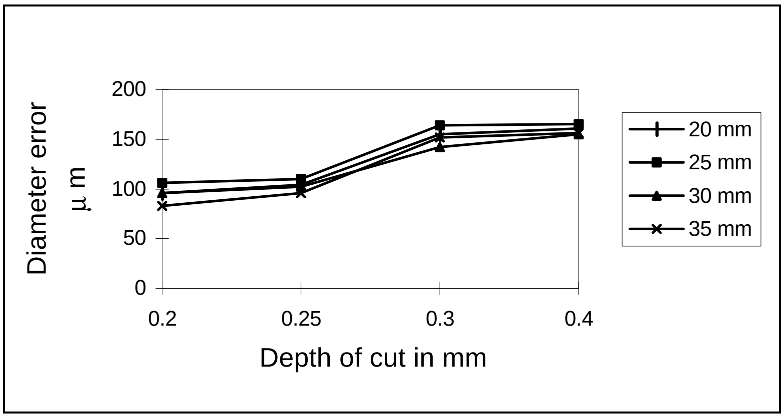

Figure 8. Effect of Depth of cut on the diameter error

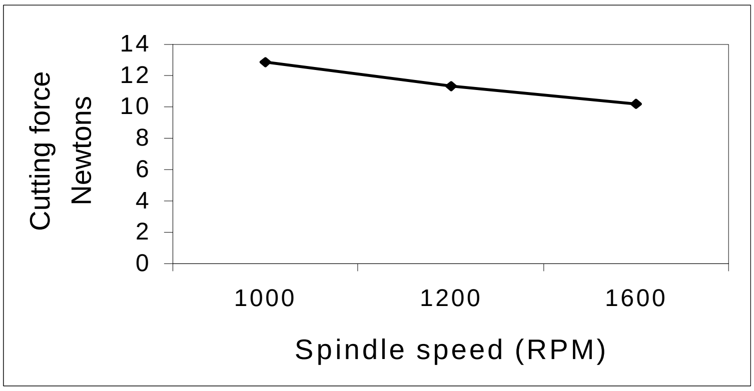

Figure 9. Effect of spindle speed on cutting force

5 CONCLUSIONS

In this work it has been established that a back-propagated single hidden layer neural network is a better modeling tool for a NC machining process. For the efficient use of the network of the configuration 6-9-2, the optimum value of the network parameters learning rate and momentum factor was found to be 0.6 and 0.9 respectively which is true for this particular case study. It was also found that the proper settings of the network parameters such as the learning rate and the performances of the BP approach such as the convergence speed depend significantly on the type of mapping problem discussed.

This work investigated the influence of the operating parameters like feed rate, depth of cut, clamping length and spindle speed . It was evident that each of these parameters studied contributed to the error in the dimensions of the machined component. Depth of cut and the feed rate had more effect on the accuracy than the other parameters. The diameter error reduces with lower values of feed rate and depth of cut, but it is necessary to determine the optimum values considering the production rate. Using the feed forward backpropagated single layer perceptron ANN, the dimensional errors and the cutting forces for preset operating conditions were predicted to close tolerances within the diameter range of 20 to 35 mm. The error tolerance was within the repeatability of the inspection system (CMM). Based on this ANN prediction, the NC program could be corrected before commencing the actual machining operation, thus improving the accuracy of the component at less cost and time.

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REFERENCES

[1] G. Chryssolouris and M. Guillot, 'A comparison of statistical and Analytical approaches to the selection of the process parameter in intelligent Machining', J. Engng. Ind.112 , 122-131(1990).
[2] S. Rangwala and D.A. Dornfeld, 'Learning and optimization of machining operations using the computing abilities of the Neural Networks', IEEE Trans. Syst. Man. Cybernetics. 19, 299—314 (1989).
[3] K. Matshushima and T. Sata, `Development in intelligent Machine Tools', J. Faculty. Eng. Tokyo, 35, 299-314(1980).
[4] H. Adeli and H.S. Park - NeuroComputing for Design and Automation-CRC press- New York
[5] D.E. RumelHart, G.E. Hinton. – 'Learning internal representations by error propagation'. Parallel Distributed Processing, MIT press. MA91986.
[6] T.W. Liao and L.J. Chen -- 'Neural Network Approach for the Grinding Operation'. – Int. J. Mach. Tool. Manu. V 34. Number 7, pp. 919 - 937, 1994.

AUTHORS: B. RAMAMOORTHY (Author to whom correspondence has to be made), V. RADHAKRISHNAN, Manufacturing Engineering Section, Department of Mechanical Engineering, Indian Institute of Technology, Madras, India
A. WECKENMANN, Department of Quality Management and Manufacturing Metrology
University of Erlangen-Nuremberg, Germany